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ARTICLE

An Energy-Efficient and Reliability-Aware Climate-Conscious Clustered Routing Framework for Sustainable Ocean Observation in Underwater Wireless Sensor Networks

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ABSTRACT: Underwater Wireless Sensor Networks (UWSNs) are exceedingly critical for large-scale underwater applications, such as environmental monitoring, infrastructure inspection, target tracking, and marine surveillance. Nevertheless, network lifetime and communication reliability are severely constrained by harsh underwater acoustic conditions, limited battery power, large propagation delays, node mobility, and uneven energy consumption. In response to these issues, this study proposes a Climate-Aware Hybrid Clustering and Routing (CA-HCR-UWSN) framework to enable sustainable, long-term underwater monitoring. This work proposes a hybrid framework that combines Elephant Herding Optimization (EHO) with the Gravitational Search Algorithm (GSA) to provide an effective solution to these challenges. To minimize unnecessary transmissions and energy usage within the clusters, a chain-oriented data aggregation mechanism based on Chain-Oriented Sensor Network (COSEN) is used, with the parameters of the climate and the underwater acoustic channel clearly taken into consideration. Moreover, a reliability-conscious inter-cluster routing policy that accounts for signal-to-noise ratio, packet error rate, and link reliability is also established to ensure reliable data delivery in a dynamic underwater environment. Extensive simulation results indicate that CA-HCR-UWSN consistently outperforms state-of-the-art protocols, including FCMMFO, MCR-UWSN, EE-UWSN, WDFAD-DBR, and EESLEPRP. The proposed framework achieves an 18%–25% increase in the network's common lifetime, a 15%–20% increase in packet delivery, 20%–26% energy savings, and a 17%–22% decrease in end-to-end delay compared with existing methods, along with better load balancing and network stability. These findings verify that CA-HCR-UWSN is a strong, scalable, and energy-efficient solution for long-term, climate-conscious underwater sensing applications.

KEYWORDS: Underwater wireless sensor networks (UWSNs); climate-aware routing; energy-efficient communication; reliability-aware networking; ocean monitoring systems; IoT-enabled marine sensing; sustainable digital ocean

1 Introduction

Underwater Wireless Sensor Networks (UWSNs) have become a fundamental enabling technology for ocean observation, environmental monitoring, offshore infrastructure inspection, target tracking, and maritime surveillance [1–3] as seen in Fig. 1. Their ability to support autonomous and continuous underwater sensing makes them indispensable for long-term marine applications. However, the unique characteristics of underwater acoustic communication, including limited bandwidth, high propagation delay, severe attenuation, high error rates, and dynamic channel conditions, significantly constrain network performance [4,5]. These challenges are further exacerbated by limited battery capacity, node mobility driven by water currents, uneven node distribution, and frequent topology changes, leading to excessive energy consumption, unreliable communication, load imbalance, and reduced network lifetime [6,7].

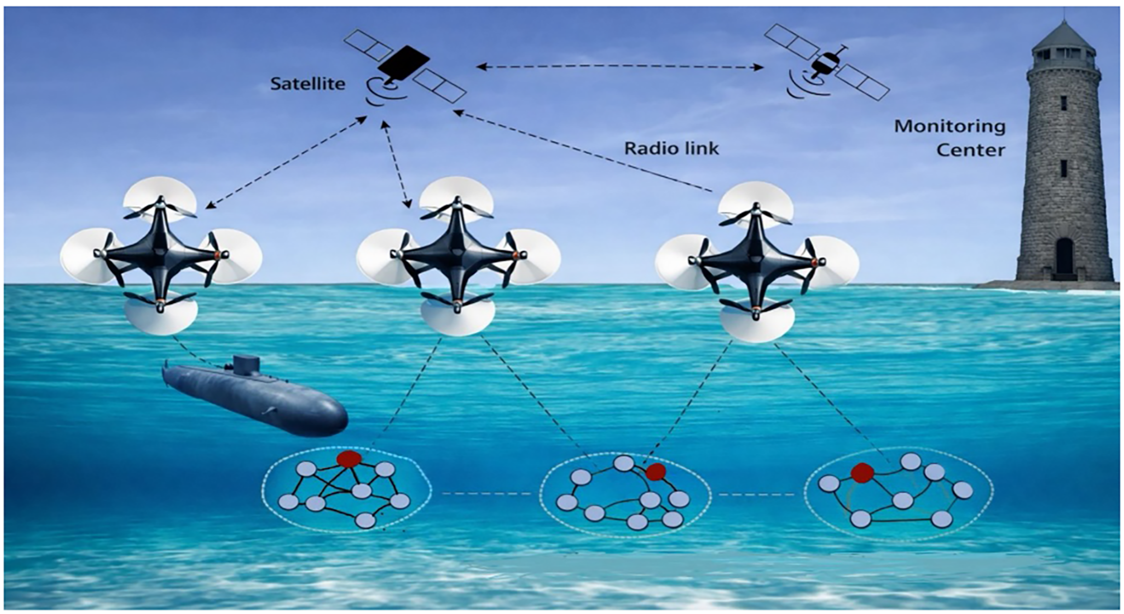

Figure 1: WSN clustering routing.

Clustering has emerged as an effective strategy for improving energy efficiency and scalability in UWSNs by reducing long-range transmissions and distributing communication overhead among sensor nodes [8–10]. Nevertheless, most existing clustering and routing protocols rely on hard clustering, static cluster-head selection, or single-objective optimization approaches, limiting their adaptability in dynamic underwater environments [11–13]. Furthermore, environmental factors such as temperature, salinity, and water currents directly influence acoustic signal propagation, link quality, and node mobility, yet these climate-related effects are rarely integrated into clustering and routing decisions. As a result, many existing protocols fail to achieve reliable and energy-efficient communication under realistic underwater conditions [14,15]. To address these limitations, this paper proposes a Climate-Aware Hybrid Clustering and Routing (CA-HCR) framework for sustainable underwater monitoring applications. The proposed framework integrates Fuzzy C-Means (FCM)-based soft clustering, hybrid Gravitational Search Algorithm–Elephant Herding Optimization (GSA-EHO) cluster-head selection, Chain-Oriented Sensor Network (COSEN)-based intra-cluster data aggregation, and reliability-aware inter-cluster routing within a unified multi-objective optimization framework. Unlike conventional approaches, CA-HCR-UWSN explicitly incorporates underwater acoustic channel characteristics and climate-related parameters into clustering, aggregation, and routing decisions. By jointly optimizing energy consumption, reliability, delay, throughput, and load balancing, the proposed framework provides a scalable, energy-efficient, and robust solution for long-term underwater sensing and ocean-monitoring applications as illustrated in Fig. 2.

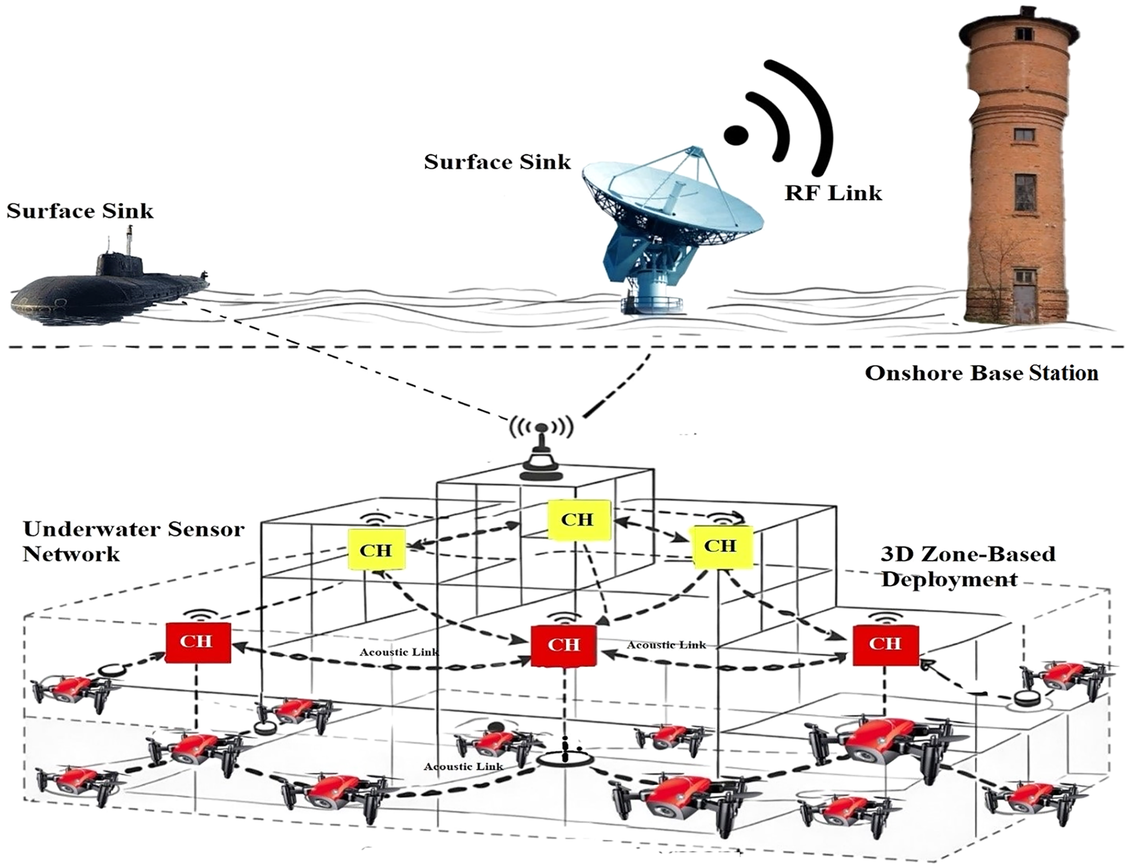

Figure 2: Network architecture of the climate-aware hybrid clustering and routing scheme for UWSNs.

Our Contributions

1. A CA-HCR-UWSN framework is proposed for reliable, energy-efficient operation in underwater wireless sensor networks.
2. FCM-based soft clustering is employed to address node mobility, uneven deployment, and dynamic underwater conditions.
3. A hybrid GSA-EHO optimization strategy is developed for stable and energy-efficient cluster-head selection.
4. A COSEN-based data aggregation mechanism is integrated to reduce redundant transmissions and communication overhead.
5. A reliability-aware routing scheme is designed using acoustic link-quality metrics, including signal-to-noise ratio (SNR), packet error rate (PER), and link reliability.
6. A multi-objective optimization framework is formulated to jointly optimize energy efficiency, delay, reliability, throughput, and load balancing for sustainable underwater monitoring.

2 Related Literature

The most important issues inUWSNs are energy efficiency, network lifetime, and reliable communication due to an adverse acoustic channel environment, limited battery capacity, long propagation delays, node mobility, and the inability to replace batteries. Many clustering, routing, and MAC-layer optimization methods have been proposed in the literature to deal with these problems. A comparative summary of existing related works in the domain of UWSNs is presented in Table 1.

Table 1: Comparative analysis of related studies in UWSNs.

Ref.	Method	Key Techniques	Main Strengths	Limitations
[6]	FCMMFO	FCM + MFO clustering	Improved energy efficiency, soft clustering	No climate awareness, no reliability modeling
[7]	MCR-UWSN	CEPOC clustering + GOA routing	Better CH selection, improved routing	Hard clustering, limited adaptability
[8]	EE-UWSNs	Energy-aware MAC + routing	Up to 68.49% energy reduction	No clustering stability, limited load balancing
[9]	GWO-based routing	Void hole detection + GWO	High PDR, void avoidance	No clustering or aggregation
[10]	EESLEPRP	ML-based routing + GMC	High PDR and throughput	High complexity, limited scalability
[11]	ED-MAC	Duty-cycled reservation MAC	Energy savings, reduced collisions	MAC-only optimization
[12]	DCO-MAC	Hybrid MAC (contention/reservation)	Improved delay and throughput	No routing or clustering support
[13]	Depth-adjusted MAC	Packet splitting + depth control	Energy reduction, higher PDR	Limited to the MAC layer
[14]	OCMAC	Reservation-based MAC	Reliable communication	Not adaptive to mobility
[15]	CSSTU-MAC	Concurrent scheduling MAC	Higher throughput	No energy-aware routing

Based on the studies above, current methods typically optimize individual aspects of clustering, routing, MAC scheduling, or void avoidance in isolation. The majority of the techniques rely on hard clustering, do not account for climate-induced acoustic differences, and do not simultaneously optimize energy, delay, reliability, throughput, or load balancing. The constraints provide the incentive to design a lightweight, climate-aware, multi-objective clustering and routing framework, which is discussed in this paper as the proposed CA-HCR-UWSN scheme.

3 Proposed Methodology

This section presents the proposed CA-HCR-UWSN framework, whose overall workflow is illustrated in Fig. 3. The framework is designed to address the major challenges of underwater wireless sensor networks, including energy constraints, communication unreliability, node mobility, load imbalance, and limited network lifetime. To achieve this, CA-HCR-UWSN integrates climate-aware acoustic modeling, soft clustering, hybrid metaheuristic optimization, chain-based data aggregation, and reliability-aware routing within a unified multi-objective optimization framework.

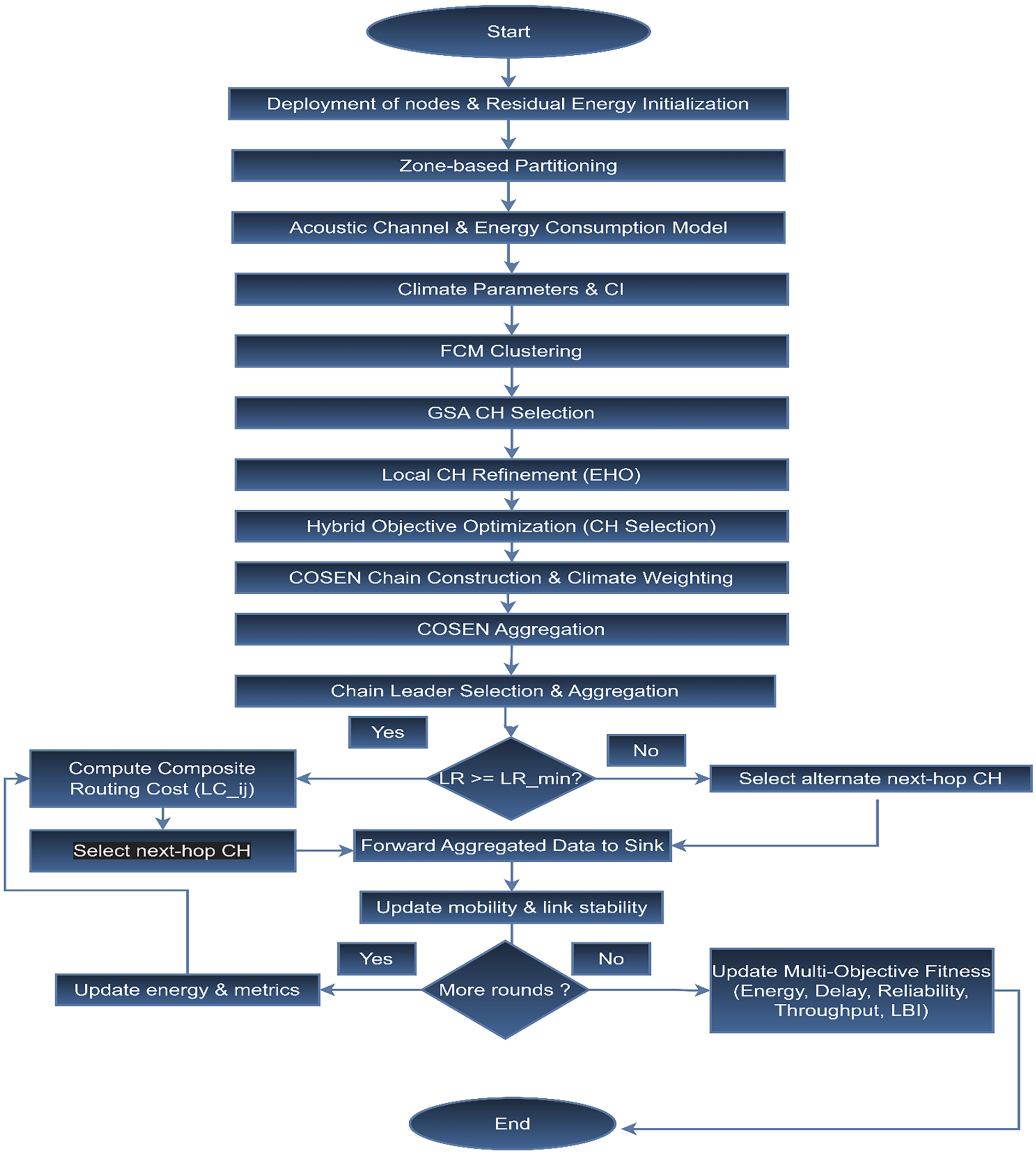

Figure 3: Flowchart of our proposed CA-HCR-UWSN framework.

Initially, sensor nodes are deployed in a three-dimensional underwater environment and organized using a zone-based architecture to reduce long-range acoustic transmissions and improve network scalability. An underwater acoustic channel and energy-consumption model are employed to estimate communication costs under realistic propagation conditions. To accommodate dynamic topology changes and node mobility, Fuzzy C-Means (FCM) clustering is used to enable flexible cluster formation via soft membership assignment.

Cluster-head selection is formulated as an optimization problem and solved using a hybrid GSA-EHO strategy, in which Gravitational Search Algorithm (GSA) performs global exploration, and EHO enhances local exploitation. To reduce redundant transmissions and communication overhead, COSEN-based chain aggregation is applied within each cluster. Furthermore, climate-related parameters, including temperature, salinity, and water current velocity, are incorporated into transmission-cost estimation and routing decisions to improve adaptability under dynamic underwater conditions. For inter-cluster communication, routing decisions are based on acoustic link-quality metrics such as signal-to-noise ratio, packet error rate, and link reliability to ensure robust data delivery. The integration of these components enables CA-HCR-UWSN to jointly optimize energy efficiency, reliability, delay, throughput, load balancing, and network lifetime, providing a scalable and sustainable solution for long-term underwater monitoring applications.

As illustrated in Fig. 3, this soft-clustering approach improves adaptability to node mobility and dynamic topology changes. Following cluster formation, cluster-head (CH) selection is formulated as an optimization problem and solved using a hybrid GSA-EHO strategy, as summarized in Algorithm 1. GSA performs global exploration by identifying energy-efficient, well-connected CH candidates based on residual energy, sink proximity, and node degree. At the same time, EHO refines candidate solutions through local exploitation while preserving diversity. The hybrid optimization process enables stable and energy-balanced CH selection.

Algorithm 1: The CA-HCR-UWSN framework

Input:

Sensor nodes N, initial energy $\boldsymbol{E_{init}}$, reliability threshold $\boldsymbol{LR_{\min}}$, maximum rounds $\boldsymbol{T_{\max}}$.

1: Deploy sensor nodes and initialize energy Eres(i) = E_{init}
2: Partition the underwater region into 3D cubical zones
3: for t = 1 to T_{max} do
4: Compute acoustic attenuation, path loss, and transmission energy
5: Apply FCM to obtain soft clusters and cluster centers
6: Select candidate cluster heads using GSA
7: Refine cluster heads using EHO
8: Optimize cluster-head selection using a hybrid objective function
9: for each cluster do
10: Construct COSEN chain based on minimum distance
11: Compute climate impact and transmission cost
12: Select chain leader
13: Aggregate data along the chain
14: Forward aggregated data to cluster head
15: end for
16: Compute SNR, BER, PER, and link reliability between cluster heads
17: Select next-hop cluster heads satisfying the reliability constraint
18: Forward data toward the sink
19: Update residual energy of nodes
20: Compute delay, throughput, and load balancing metrics
21: end for
22: return Network lifetime, energy consumption, and performance results

Subsequently, COSEN-based intra-cluster aggregation is employed to reduce redundant transmissions and communication overhead. Sensor nodes are organized into chains based on neighborhood proximity, and climate-aware weighting factors derived from temperature, salinity, and water current velocity are incorporated into transmission cost estimation. Aggregated data are forwarded through a chain leader selected according to residual energy and communication cost. For inter-cluster communication, routing decisions are performed using acoustic link-quality metrics, including SNR, bit error rate (BER), PER, and link reliability. This reliability-aware routing strategy improves packet delivery performance while reducing retransmissions and energy consumption under dynamic underwater conditions.

To ensure reliable inter-cluster communication, a minimum reliability threshold is enforced to exclude unstable links and reduce retransmissions. The next-hop cluster head is selected based on link reliability and a composite routing cost that incorporates distance, residual energy, packet error rate, link reliability, and climate impact. Aggregated data are forwarded hop-by-hop to the surface sink and subsequently delivered to the monitoring station. The proposed framework evaluates network performance using key metrics, including energy consumption, end-to-end delay, throughput, load-balancing index, and network lifetime. Node mobility and link dynamics induced by water currents are explicitly considered to enhance robustness under realistic underwater conditions. Furthermore, the overall framework is formulated as a multi-objective optimization problem that jointly optimizes energy efficiency, reliability, delay, throughput, and load balancing. By integrating climate-aware modeling, hybrid GSA-EHO optimization, COSEN-based aggregation, and reliability-aware routing, CA-HCR-UWSN provides a scalable, energy-efficient, and reliable solution for long-term underwater monitoring applications.

3.1 Underwater Acoustic Channel and Energy Model

Underwater acoustic communication is highly sensitive to transmission distance and signal frequency. To realistically model signal attenuation in the underwater environment, the acoustic path loss is formulated as a function of distance d and frequency f, as given in Eq. (1). The absorption coefficient defined in Eq. (2) captures frequency-dependent losses caused by boric acid relaxation, magnesium sulfate relaxation, and pure water viscosity. The total acoustic path loss in decibels, expressed in Eq. (3), combines geometric spreading and absorption losses. Based on this model, the minimum transmission power required to ensure reliable reception is derived in Eq. (4). Using this transmission power, the energy consumption for data transmission, reception, and aggregation is calculated using Eqs. (5)–(7). This energy model enables accurate estimation of node-level energy consumption under realistic underwater acoustic conditions and serves as the foundation for energy-aware clustering and routing decisions. Underwater acoustic signal attenuation depends on transmission distance d and signal frequency f and is modeled as:

$$A\left(d,f\right)=d_k\cdot a\left(f\right)^d \tag{1}$$

where k is the spreading factor (typically $k=2$ for spherical spreading), and $a(f)$ represents the frequency-dependent absorption coefficient. The absorption coefficient is defined as:

$$a\left(f\right)=\frac{0.11f^2}{1+f^2}+\frac{44f^2}{4100+f^2}+2.75\times10^{-4}f^2+0.003 \tag{2}$$

This expression captures absorption losses due to boric acid relaxation, magnesium sulfate relaxation, and pure water viscosity. The total acoustic path loss in decibels (dB) is computed as:

$$PL\left(d,f\right)=10klogd+d\cdot10loga(f) \tag{3}$$

The transmission power required to ensure a minimum received power P_0 is given by:

$$P_{tx} = P_0 \cdot d^2 \cdot 10^{\alpha}(f)/10 \tag{4}$$

The energy consumed to transmit k bits over a distance d is:

$$E_{tx}(k,d) = k(E_{elec} + P_{tx}) \tag{5}$$

where E_{elec} denotes electronic circuitry energy consumption.

The reception and data aggregation energies are defined as:

$$E_{rx}(k) = k \cdot P_{rx} \tag{6}$$

$$E_{agg}(k) = k \cdot E_{DA} \tag{7}$$

3.2 Network and Zone-Based Deployment Model

To reduce long-range acoustic transmissions and improve scalability, the underwater monitoring region is partitioned into equal-sized three-dimensional cubical zones. Each sensor node is assigned to a zone using Eq. (8) based on its spatial coordinates in the horizontal and depth dimensions. This zone-based deployment limits communication to nearby nodes, reduces transmission distance, and mitigates energy holes. The sink node is positioned above the water surface and may be dynamically relocated to further balance energy consumption across the network. The underwater monitoring area is partitioned into equal-sized 3D cubical zones to minimize long-range transmissions. Each sensor node I is mapped to a zone $S_{i,b}$ as:

$$\mathrm{S_{i,b}} = (\mathrm{z}-1)\,\mathrm{n}^2 + (\mathrm{y}-1)\mathrm{n} + \mathrm{x} \tag{8}$$

where x, y, z represent zone indices along horizontal and depth dimensions, and n denotes the number of zones per dimension. The sink node is positioned above the water surface and may be dynamically relocated to prevent energy holes.

3.3 Initial Soft Clustering Using Fuzzy C-Means (FCM)

To address node mobility and the uncertainty of the underwater topology, Fuzzy C-Means (FCM) clustering is employed. Unlike hard clustering, FCM assigns each node a membership degree u_{ij} to multiple clusters, as defined in Eq. (9). This soft assignment allows nodes to adapt their cluster affiliations in the presence of mobility and uneven deployment. Cluster centers are iteratively updated using Eq. (10), and clustering quality is optimized by minimizing the objective function in Eq. (11). The optimal number of clusters is selected using the elbow method to balance clustering accuracy and overhead.

To address uncertain underwater topology and node mobility, FCM assigns each node ia membership degree. u_{ij} for cluster j:

$$\sum_{j=1}^{c} u_{ij} = 1, u_{ij} \in [0,1] \tag{9}$$

Cluster centers are updated iteratively as:

$$Vj = \frac{\sum_{i=1}^{N} u_{ij}^{m} Xi}{\sum_{i=1}^{N} u_{ij}^{m}} \tag{10}$$

where m is the fuzzification coefficient and X_i denotes node position.

The clustering objective function is:

$$J = \sum_{i=1}^{N} \sum_{j=1}^{c} u_{ij}^{m} \|X_i - V_j\|^2 \tag{11}$$

The optimal number of clusters c is determined using the elbow method based on marginal reductions in J.

3.4 Global Cluster-Head Exploration Using GSA

After initial clustering, the GSA is applied to explore globally optimal cluster-head (CH) candidates. Each node is modeled as a GSA agent, represented by its position vector in the solution space (Eq. (12)). The fitness function in Eq. (13) evaluates each node based on residual energy, distance to the sink, and node degree, ensuring energy-efficient and well-connected CH selection. Agent masses are computed using Eq. (14), and gravitational interactions among agents guide the search toward optimal solutions through Eqs. (15)–(18). GSA provides strong global exploration capability, preventing premature convergence to suboptimal CH selections.

Each sensor node is modeled as a GSA agent:

$$P\_i = \left(p_i^1, p_i^2, \ldots, p_i^D\right) \tag{12}$$

The fitness of node i at iteration t is computed as:

$$Fitness_i\left(t\right) = \alpha \frac{Eres}{iEinit}, i + \beta \frac{1}{di, sink} + \gamma \cdot Degree_i \tag{13}$$

Subject to $\alpha + \beta + \gamma = 1$, balancing residual energy, proximity to sinks, and connectivity.

The agent mass is calculated as:

$$m_i\left(t\right) = \frac{Fitness_i\left(t\right) - worst\left(t\right)}{\left(best\left(t\right) - worst\left(t\right)\right)} \tag{14}$$

The gravitational force acting on agent i in dimension d is:

$$F_i^d\left(t\right) = \sum_{j \in K_{best}} rand_j . G\left(t\right) \frac{M_i\left(t\right) M_j\left(t\right)}{R_{ij}\left(t\right)} \left(x_j^d - x_i^d\right) \tag{15}$$

The acceleration, velocity, and position updates are:

$$a_i^d\left(t\right) = \frac{F_i^d\left(t\right)}{M_i\left(t\right)} \tag{16}$$

$$v_i^d\left(t+1\right) = rand \cdot v_i^d\left(t\right) + a_i^d\left(t\right) \tag{17}$$

$$x_i^d\left(t+1\right) = x_i^d\left(t\right) + v_i^d\left(t+1\right) \tag{18}$$

3.5 Cluster-Head Refinement Using Elephant Herding Optimization (EHO)

To further optimize the choice of CH, Elephant Herding Optimization (EHO) is used as a local optimization step. Treatment: Every cluster is regarded as an elephant clan, and candidate CH positions are updated by applying Eq. (19) using the clan center computed in Eq. (20). To maintain population diversity and prevent stagnation, the weakest candidates are reintegrated using Eq. (21). This hybrid GSA-EHO approach combines global-scale exploration and local-scale exploitation to find stable, energy-efficient CHs.

Each cluster is treated as an elephant clan. The position update rule is:

$$X_{i,j}^{t+1} = X_{best,j}^{t} + \alpha\left(X_{center,j}^{t} - X_{i,j}^{t}\right) \tag{19}$$

The clan center is calculated as:

$$X_{center}, j = \frac{1}{n_j}\sum_{i=1}^{n_j} X_{i}, _j \tag{20}$$

To maintain population diversity, the weakest candidates are randomly repositioned:

$$\mathrm{X_{worst}} = \mathrm{X_{min}} + \mathrm{rand}\left(\mathrm{X_{max}} - \mathrm{X_{min}}\right) \tag{21}$$

3.6 Hybrid Optimization Objective Function

The CH selection problem is formulated as a weighted multi-objective optimization function in Eq. (22), incorporating intra-cluster distance, CH-to-sink distance, and total energy consumption. A sigmoid normalization function (Eq. (23)) ensures balanced metric scaling. This formulation enables adaptive trade-offs among competing objectives, improving overall network performance.

The CH selection problem is formulated as:

$$F_{obj} = w_1.dist_{CM} + w_2.dist_{CH-sink} + w_3.E_{total} \text{ where } w_1 + w_2 + w_3 = 1 \tag{22}$$

Metric normalization is achieved using a sigmoid function:

$$S(x) = \frac{1}{1 + e^{-x}} \tag{23}$$

3.7 COSEN-Based Intra-Cluster Data Aggregation

3.7.1 Chain Construction

Within each cluster, sensor nodes are arranged into a chain based on minimum neighbor distance (Eq. (24)), forming the chain structure defined in Eq. (25). Nodes are arranged into a chain based on minimum neighbor distance:

$$d_{i,i+1} = min\{\|X_i - X_k\|\} \tag{24}$$

The resulting chain is:

$$C_j = \{n_1 \rightarrow n_2 \rightarrow \ldots \rightarrow n_{N_j}\} \tag{25}$$

3.7.2 Climate-Aware Chain Weighting

Each node is assigned a climate impact factor based on temperature, salinity, and water current velocity (Eq. (26)). The effective transmission cost is computed in Eq. (27), enabling climate-aware energy estimation. Each node is assigned a climate impact factor:

$$CI_i = \eta_1 T_i + \eta_2 S_i + \eta_3 V_i \tag{26}$$

with $\sum \eta k = 1$. The effective transmission cost is:

$$EC_{i,i+1} = d_{i,i+1}.CI_i \tag{27}$$

The climate-aware component directly influences underwater acoustic communication performance through its impact on signal propagation characteristics and node mobility. Variations in water temperature and salinity affect sound speed, absorption loss, and acoustic attenuation, whereas water currents influence node movement, link stability, and communication reliability. Consequently, the climate impact factor is incorporated into the transmission-cost estimation and routing process, enabling the proposed framework to adapt its clustering, aggregation, and forwarding decisions according to prevailing environmental conditions. This adaptation improves energy efficiency and communication reliability in dynamic underwater environments.

3.7.3 Aggregation Energy Model

The energy consumed during COSEN-based aggregation is computed using Eqs. (28) and (29). The energy consumed during COSEN aggregation is:

$$E_{COSEN,i} = E_{rx}(k) + E_{agg}(k) + E_{tx}(k, d_{i,i+1}) \tag{28}$$

The total aggregation energy per cluster is:

$$E^{j}_{COSEN} = \sum_{i=1}^{N_j-1} E_{COSEN,i} \tag{29}$$

3.7.4 Chain Leader Selection

The chain leader is selected using Eq. (30), prioritizing nodes with higher residual energy and lower transmission cost. COSEN aggregation minimizes redundant transmissions and balances intra-cluster energy consumption.

The chain leader is selected as:

$$CL_j = argmax_i \left(\frac{E_{res,i}}{EC_{i,i+1}.\,|H_i - H_{CH}|} \right) \tag{30}$$

3.8 COSEN-to-CH Forwarding

The aggregated data packet is forwarded from the chain leader to the cluster head using the energy model in Eq. (31), thereby ensuring efficient intra-cluster communication. The aggregated packet is forwarded to the CH with energy cost:

$$E_{CL\rightarrow CH} = E_{tx}(k, d_{CL,CH}) \tag{31}$$

3.9 Reliability-Aware Inter-Cluster Routing

Inter-cluster routing decisions incorporate acoustic link quality metrics. Signal-to-noise ratio, bit error rate, packet error rate, and link reliability are computed using Eqs. (32)–(36). Only links satisfying the reliability constraint in Eq. (37) are considered, and the next hop is selected using Eq. (38). This ensures stable and dependable packet forwarding under dynamic underwater conditions.

3.9.1 Signal-to-Noise Ratio

The SNR reflects the quality of the acoustic signal in the presence of underwater attenuation and ambient noise. A higher SNR bespeaks stronger signal reception and improved communication reliability. In the proposed framework, SNR is computed from the received signal power and environmental noise, serving as the primary indicator of acoustic channel quality between neighboring cluster heads.

$$P_{rx,ij} = \frac{P_{tx,i}}{A(d_{ij}, f)} \tag{32}$$

$$SNR_{ij} = \frac{P_{rx,ij}}{N_0.B} \tag{33}$$

3.9.2 Bit Error Rate (BER)

The BER quantifies the probability of bit-level transmission errors induced by noise, fading, and interference in underwater acoustic channels. The SNR directly influences BER and provides an estimate of link reliability at the physical layer. Lower BER values indicate more stable, error-resilient communication links.

$$BER_{ij} = \frac{1}{2} erfc\left(\sqrt{SNR_{ij}}\right) \tag{34}$$

3.9.3 Packet Error Rate (PER)

The PER extends bit-level error analysis to the packet level by accounting for packet length. PER constitutes the likelihood of complete packet loss during transmission and is a more realistic indicator of communication performance in UWSNs. Lower PER values represent higher packet delivery success.

$$PER_{ij} = 1 - (1 - BER_{ij})^L \tag{35}$$

3.9.4 Link Reliability

Link reliability (LR) is derived from the packet error rate and represents the probability of successful packet delivery over an inter-cluster link. This metric captures the combined effects of channel attenuation, noise, and packet size, furnishing a comprehensive measure of link stability under dynamic underwater conditions.

$$LR_{ij} = 1 - PER_{ij} \tag{36}$$

3.9.5 Reliability Constraint

To avoid unstable or unreliable routes, a minimum reliability threshold is enforced during inter-cluster routing. Only links fulfilling the reliability constraint are considered for packet forwarding. This mechanism forestalls excessive retransmissions, reduces energy wastage, and enhances overall network stability.

$$LR_{ij} \geq LR_{min} \tag{37}$$

3.9.6 Next-Hop Selection

Among all neighboring cluster heads that satisfy the reliability constraint, the next hop is selected based on maximum link reliability. By prioritizing highly reliable links, the proposed routing strategy ensures dependable data delivery, minimizes packet loss, and improves network robustness in dynamic underwater environments.

$$j^* = arg\,min_{j \in N_i} \left(\frac{1}{LR_{ij}} \right) \tag{38}$$

3.10 Composite Routing Cost Function

The composite routing cost in Eq. (39) jointly accounts for distance, residual energy, packet error rate, link reliability, and climate impact, thereby enabling adaptive next-hop selection.

$$LC_{ij} = \lambda_1 d_{ij} + \lambda_2 \frac{1}{E_{res,j}} + \lambda_3 PER_{ij} + \lambda_4 \frac{1}{LR_{ij}} + \lambda_5 CI_j \tag{39}$$

3.11 Delay and Throughput Modeling

End-to-end delay and network throughput are modeled using Eqs. (40) and (41), capturing propagation, transmission, and queuing delays.

$$D_{e2e} = \Sigma(D_{prop} + D_{tx} + D_{queue}) \tag{40}$$

$$T_{net} = \frac{\sum L_{recv}}{D_{e2e}} \tag{41}$$

3.12 Load Balancing Analysis

Load balancing is quantified using the Load Balancing Index (Eq. (42)), which measures fairness in node participation across clusters.

$$LBI = \frac{(\sum N_j)^2}{c \sum {N_j}^2} \tag{42}$$

3.13 Mobility and Link Stability

Node mobility is modeled using Eq. (43), and link stability is quantified using Eq. (44), ensuring robustness under water-current–driven movement.

$$X_i(t+1) = X_i(t) + v_i \Delta t + \frac{1}{2} a_i \Delta t^2 \tag{43}$$

$$LS_{ij} = \frac{1}{|v_i - v_j|} \tag{44}$$

3.14 Multi-Objective Optimization

Finally, the proposed framework formulates a multi-objective optimization problem in Eqs. (45) and (46), jointly optimizing energy consumption, delay, reliability, throughput, and load balancing.

$$F = [E_{total}, D_{e2e}, PER, 1/T_{net}, 1/LBI] \tag{45}$$

$$F_{scalar} = \Sigma \mu_k F_k \tag{46}$$

Although link reliability is the primary criterion for next-hop selection, routing decisions are influenced by the broader multi-objective optimization framework. Cluster-head selection, chain formation, transmission-cost estimation, and energy management jointly consider energy efficiency, delay, throughput, and load balancing. Consequently, reliability-aware routing operates within a framework optimized across multiple performance objectives rather than as an isolated routing mechanism. By integrating climate-aware modeling, hybrid GSA-EHO optimization, COSEN-based aggregation, and reliability-aware routing, CA-HCR-UWSN provides a scalable, energy-efficient, and reliable solution for sustainable long-term underwater monitoring applications.

4 Results and Discussion

This section evaluates the performance of the proposed CA-HCR-UWSN framework and compares it with state-of-the-art protocols, including MCR-UWSN [7], EE-UWSN [8], WDFAD-DBR [9], and EESLEPRP [10]. The evaluation considers key UWSN performance metrics, namely network lifetime, load-balancing index, end-to-end delay, residual energy, packet delivery ratio (PDR), and node survivability. Simulations were conducted in MATLAB R2023a using a three-dimensional underwater acoustic network deployed over a 500 m × 500 m × 50 m monitoring area with 150 randomly distributed sensor nodes and a surface sink. Each simulation was executed 20 times, and the reported results represent the average performance. To ensure a fair comparison, all protocols were evaluated under identical network topology, node density, traffic conditions, mobility assumptions, and underwater acoustic channel settings. The acoustic channel model incorporates frequency-dependent attenuation and a propagation speed of 1500 m/s. It should be noted that the benchmark protocols were implemented according to their original configurations reported in the literature. Unlike these approaches, the proposed CA-HCR-UWSN explicitly incorporates environmental factors, including temperature, salinity, and water-current velocity, into clustering, aggregation, and routing decisions. The simulation parameters used in the evaluation are summarized in Table 2.

Table 2: Simulation parameters.

Parameter	Value	Parameter	Value
Network environment	Underwater acoustic (3D)	Energy per bit	50 nJ/bit
Network size	500 m × 500 m × 50 m	Amplification energy factor	100 pJ/bit/m^2
Number of sensor nodes	150	Simulation rounds	1200
Reception power	0.1 W	Node deployment	Random uniform
Initial energy of the sensor node	5 J	Communication radius	50 m
Initial energy of the sink	1000 J	Data packet size	200 bits
Transmission power	2 W	Acoustic carrier frequency	30 kHz

4.1 Network Lifetime Analysis

Fig. 4 shows the network lifetime performance based on the First Node Death (FND), Half Node Death (HND), and Last Node Death (LND).

The proposed CA-HCR-UWSN achieves the highest network lifetime across the FND, HND, and LND metrics, demonstrating superior energy management and network stability. The delayed occurrence of FND indicates balanced early-stage energy consumption, primarily due to FCM-based soft clustering and hybrid GSA-EHO cluster-head selection. Similarly, the extended HND and LND values confirm the framework's ability to sustain network operation under prolonged communication activity and node failures. In contrast, WDFAD-DBR [9] and EESLEPRP [10] exhibit earlier node depletion owing to uneven forwarding loads and accelerated energy consumption at critical relay nodes. Although MCR-UWSN [7] improves network lifetime compared with conventional depth-based approaches, its hard-clustering mechanism limits adaptability to node mobility and dynamic underwater conditions. These results demonstrate the effectiveness of the proposed framework in balancing energy consumption and prolonging network lifetime.

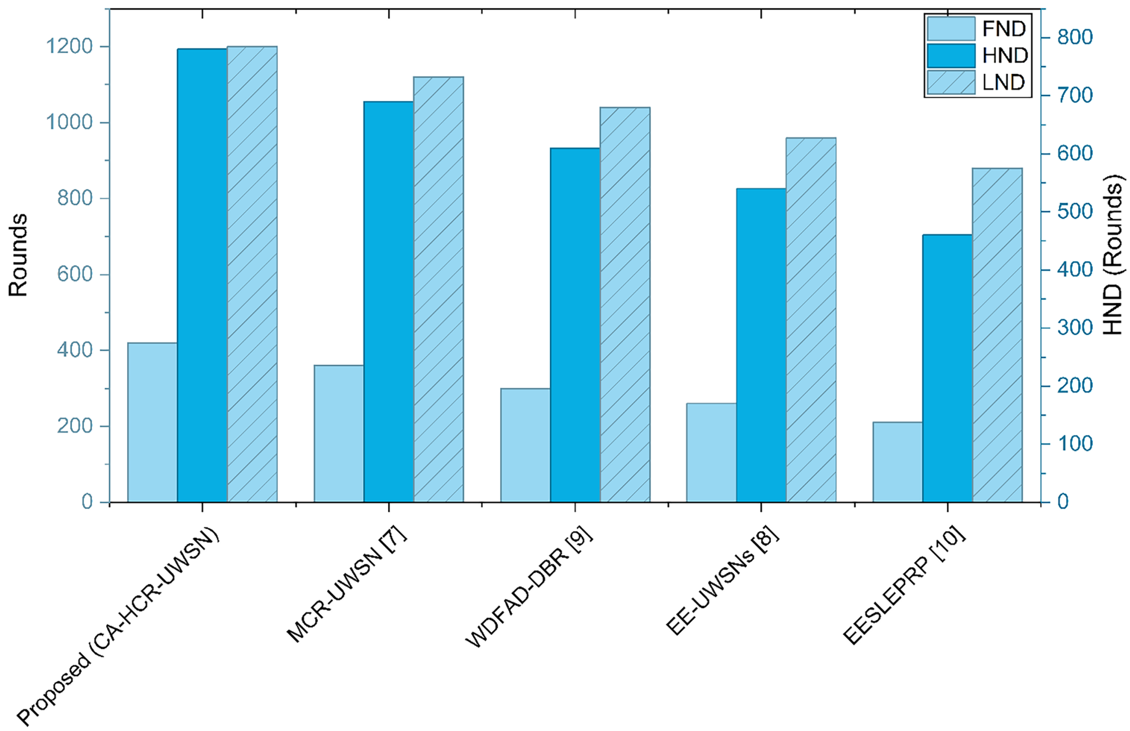

Figure 4: Network lifetime analysis [7–10].

4.2 Load Balancing Performance

Fig. 5 compares the load-balancing performance of the evaluated protocols. CA-HCR-UWSN consistently achieves the highest load-balancing index throughout the simulation, maintaining values above 0.90 even at later stages. This indicates effective workload distribution and balanced energy consumption among sensor nodes. In contrast, the benchmark protocols exhibit a progressive decline in load-balancing performance due to uneven energy depletion and cluster-head overloading. These results demonstrate the effectiveness of the proposed framework in improving network stability and resource utilization.

4.3 End-to-End Delay Evaluation

Fig. 6 is a representation of the results of the end-to-end delay over communication rounds. The delay time gradually increases with each protocol due to energy loss and network load. Nevertheless, the delay of the proposed CA-HCR-UWSN remains the lowest at every round at 0.32–0.34 s, and lower than the delay in MCR-UWSN (0.35 s), EE-UWSNs (0.38 s), EESLEPRP (0.42 s), and WDFAD-DBR (0.46 s) at 0 rounds (0–200 rounds) and at 800 rounds or higher (0.5–2.0 rounds). Conversely, the proposed approach does not exceed 0.46 s of delay even in 1200 rounds

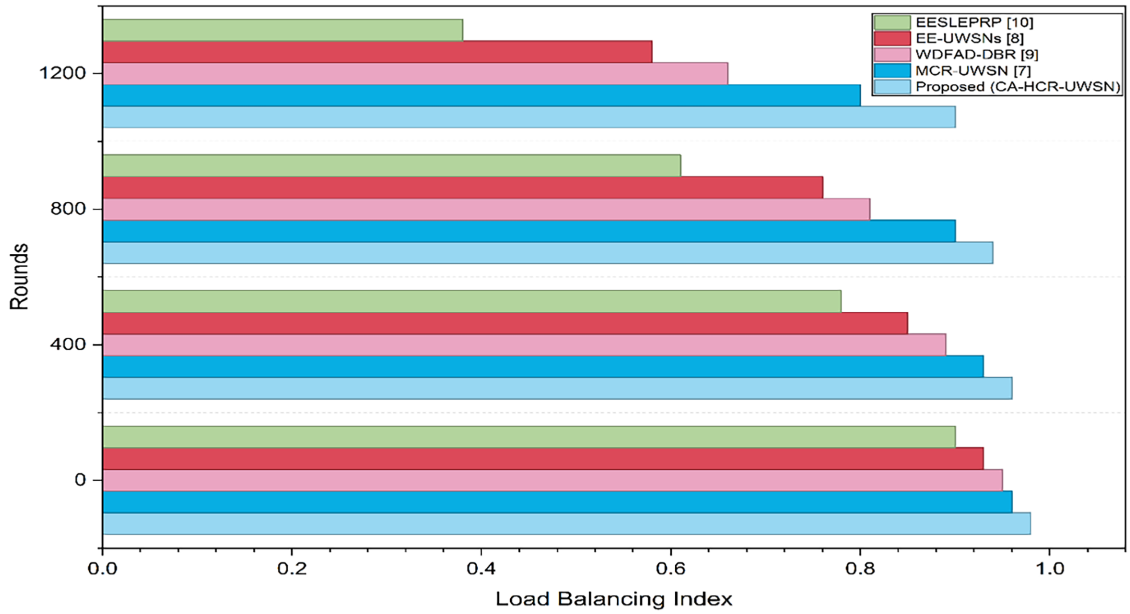

Figure 5: Load balancing analysis [7–10].

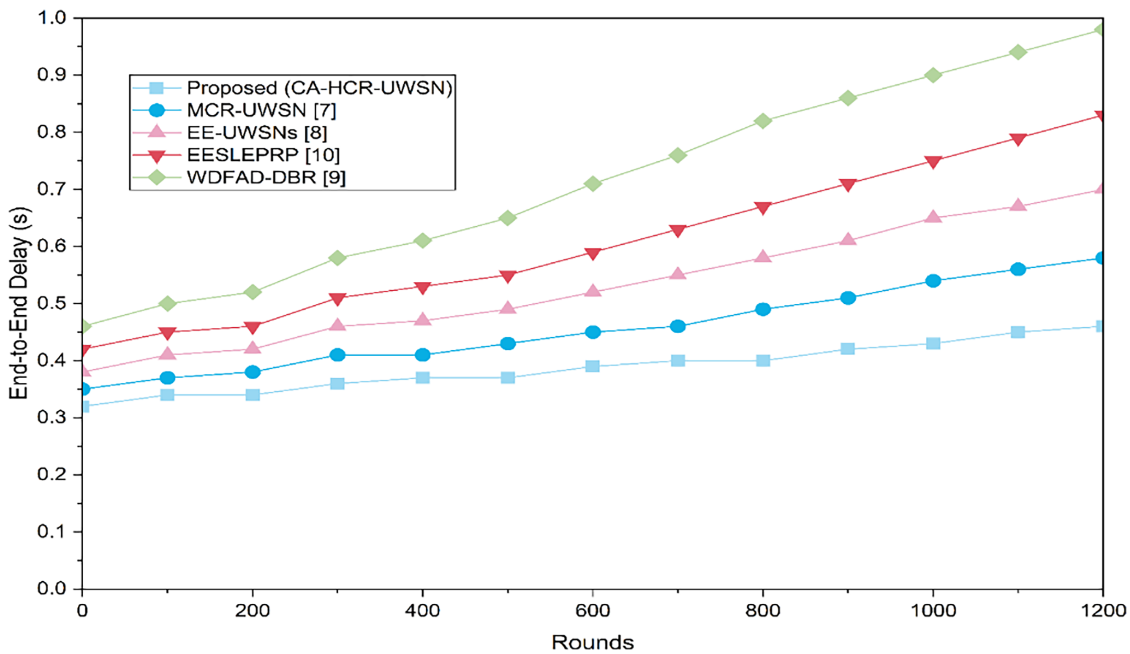

Figure 6: End-to-End delay vs. rounds [7–10].

4.4 Residual Energy Analysis

Fig. 7 illustrates the amount of residual energy after 1200 rounds. At the beginning of all the protocols, there is an equal amount of energy (~5 J).

Patterns of energy depletion, however, differ markedly, as our proposed CA-HCR-UWSN has the lowest energy depletion rate. It has virtually 4 J of residual energy even after 600 rounds, whereas other schemes, including WDFAD-DBR and EESLEPRP, are nearly depleted at 1000 rounds. On the other hand, the suggested scheme still has 2.8 J of energy, indicating that the energy is better conserved. After 1200 rounds, all the schemes have significantly lost energy, but the proposed scheme still has much higher residual energy than the others.

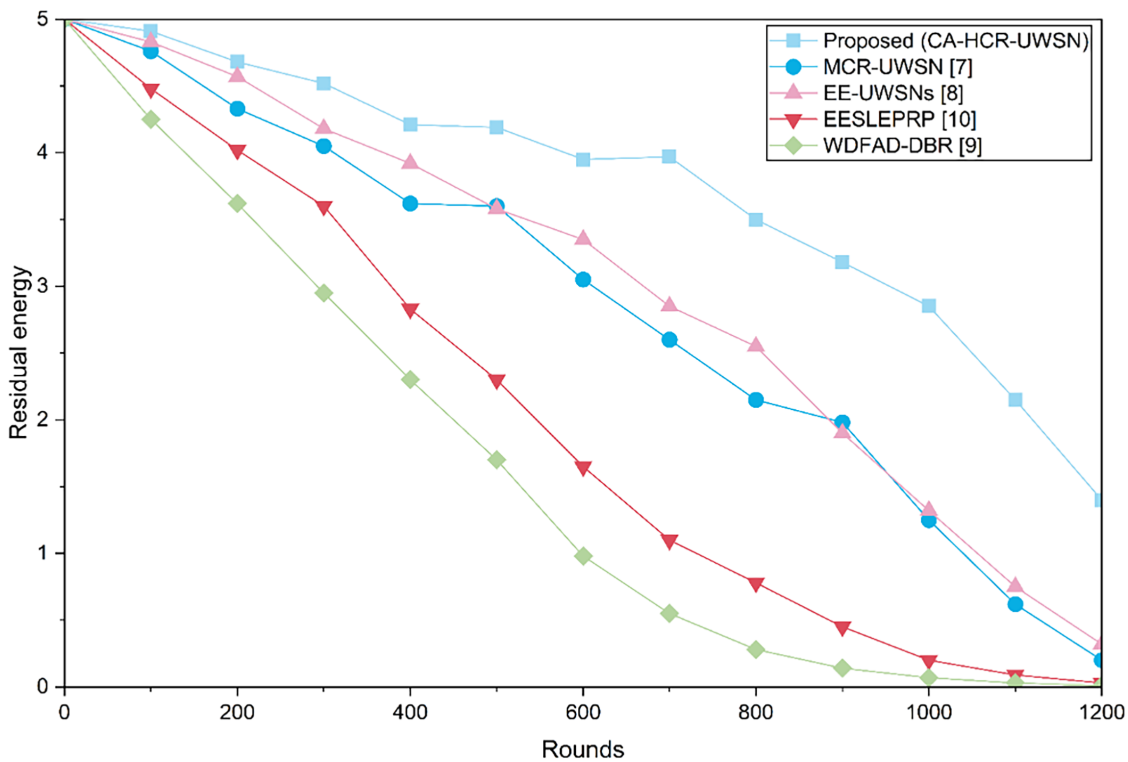

Figure 7: Residual energy vs. rounds [7–10].

4.5 Packet Delivery Ratio (PDR)

The packet delivery ratio indicates network performance and network development as demonstrated in Fig. 8.

The proposed CA-HCR-UWSN achieves the highest PDR across all rounds. In later phases of the simulation, consistent packet delivery is maintained through link-quality-aware routing and fair energy consumption. This is demonstrated by competing protocols (especially EESLEPRP [10]) and WDFAD-DBR [9], which show that the PDR decreases sharply with the number of node failures and the emergence of regions of nothingness. The non-linear yet smooth PDR degradation demonstrates the reality of underwater channel behavior and the robustness of the proposed method.

4.6 Alive Nodes Ratio

The alive node-to-time ratio is indicated in Fig. 9. CA-HCR-UWSN has a higher percentage of active nodes throughout the simulation, which is directly proportional to better lifetime and energy savings. The progressive node-failure regime, rather than sudden failures, indicates stable clustering and managed energy consumption. It also confirms that hybrid optimization and climate-aware routing effectively increase network survivability.

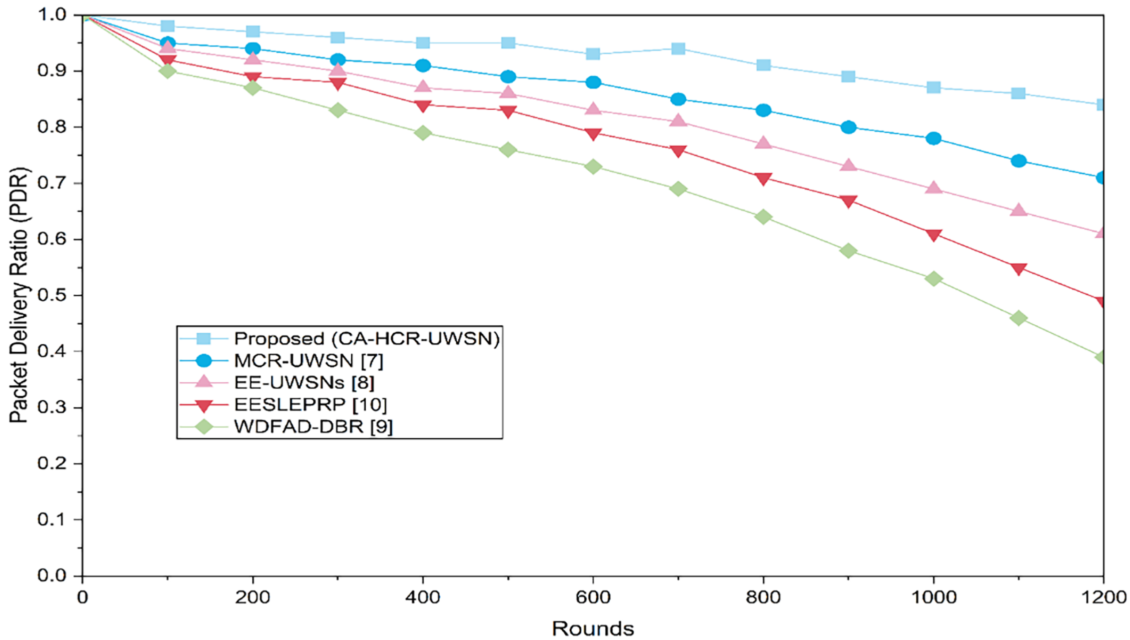

Figure 8: Packet delivery ratio vs. rounds [7–10].

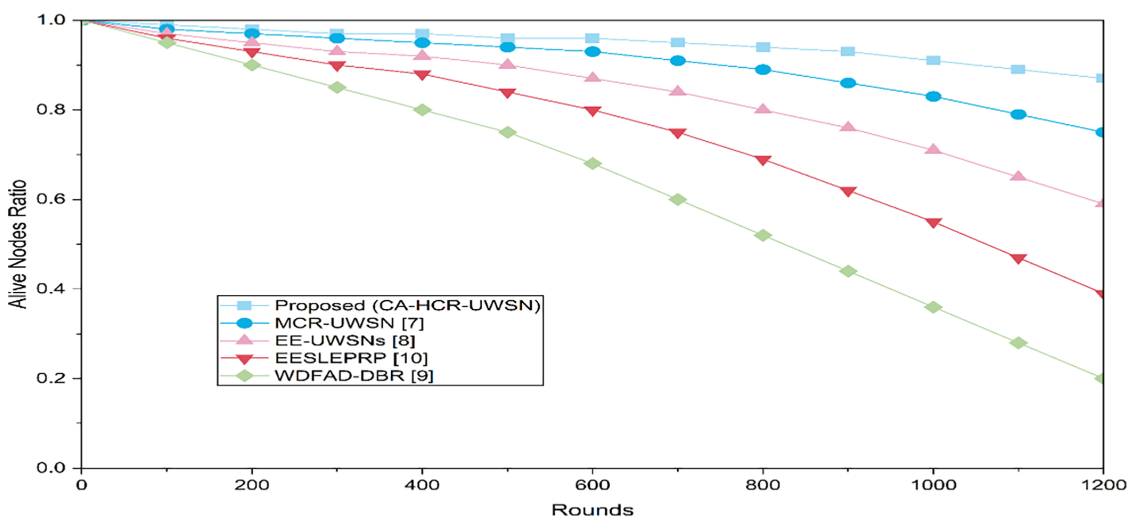

Figure 9: Alive nodes ratio vs. rounds [7–10].

4.7 Overall Consistency of Results

Fig. 10 presents a normalized performance comparison of all the measures considered. The proposed CA-HCR-UWSN consistently outperforms all benchmark protocols in network lifetime, load-balancing efficiency, residual energy, packet delivery ratio, node survivability, and end-to-end delay. The balanced and expanded radar profile shows that improving one metric will not negatively affect other metrics, demonstrating that CA-HCR-UWSN is a holistic and sustainable optimization solution, not performance gains in isolation, and that it is highly applicable to long-term, large-scale underwater monitoring tasks.

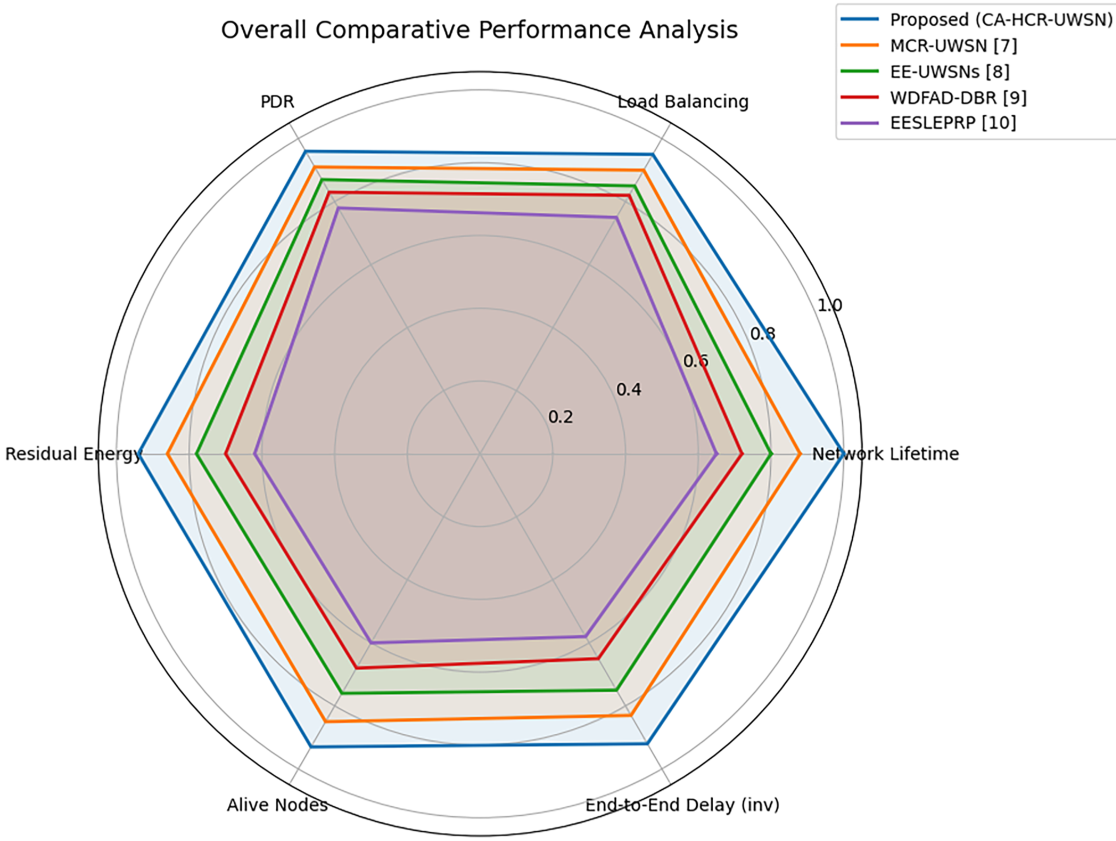

Figure 10: Overall performance comparison of evaluated protocols [7–10].

5 Discussion

The proposed CA-HCR-UWSN framework addresses key challenges in underwater wireless sensor networks, including energy inefficiency, load imbalance, unreliable communication, and limited network lifetime. The superior performance of the framework can be attributed to the synergistic integration of climate-aware modeling, hybrid GSA-EHO optimization, COSEN-based aggregation, and reliability-aware routing. The combination of FCM-based soft clustering and hybrid cluster-head selection enables balanced energy consumption. It reduces premature node failures, thereby extending network lifetime and improving load-balancing performance. Furthermore, COSEN-based aggregation minimizes redundant transmissions and communication overhead, thereby reducing energy consumption and increasing residual energy throughout network operation.

The reliability-aware routing mechanism enhances network performance by incorporating acoustic link-quality metrics, including signal-to-noise ratio, packet error rate, and link reliability. By avoiding unstable communication links, the proposed framework reduces retransmissions and end-to-end delay while maintaining a high packet delivery ratio. The consistent improvements across multiple performance metrics indicate the effectiveness of the proposed framework in achieving balanced network optimization. Environmental parameters, including temperature, salinity, and water-current velocity, influence acoustic attenuation, link stability, and node mobility; therefore, they are incorporated into clustering, aggregation, and routing decisions to improve communication reliability under dynamic underwater conditions. In practical deployments, these parameters can be obtained through onboard oceanographic sensors, autonomous underwater vehicles (AUVs), surface buoy systems, or external ocean-monitoring databases, enabling adaptive network operation in changing marine environments.

The hybrid GSA-EHO optimization strategy combines the global exploration capability of GSA with the local exploitation strength of EHO, enabling robust cluster-head selection and improved energy balancing. GSA efficiently explores the global search space to identify promising cluster-head candidates. In contrast, EHO refines these solutions based mechanisms that preserve local and population diversity. This complementary behavior reduces premature convergence and improves the stability of cluster-head selection in dynamic underwater environments. The improvements in network lifetime, residual energy, and load-balancing performance suggest the effectiveness of the hybrid optimization strategy. Nevertheless, a dedicated comparative analysis involving standalone GSA, standalone EHO, and the hybrid GSA-EHO approach will be considered in future work to provide a more comprehensive assessment of their respective contributions and performance advantages. The simulation framework incorporates climate-aware parameters through acoustic attenuation modeling, transmission-cost estimation, mobility modeling, and routing decisions, thereby reflecting the influence of environmental conditions on network behavior. While the current study considers a representative underwater monitoring scenario, future work will investigate the performance of the proposed framework under a broader range of temperature, salinity, and water-current conditions to further evaluate its adaptability and robustness across diverse marine environments. Additional validation through real-world deployments and extended environmental sensitivity analyses will further strengthen the practical applicability of the proposed framework.

6 Conclusion and Future Scope

This studyproposes CA-HCR-UWSN, a climate-aware hybrid clustering and routing framework for underwater wireless sensor networks. The framework integrates FCM-based soft clustering, hybrid GSA-EHO cluster-head selection, COSEN-based data aggregation, and reliability-aware routing within a unified multi-objective optimization framework. Simulation results demonstrated that CA-HCR-UWSN consistently outperforms existing protocols across network lifetime, energy efficiency, load balancing, packet delivery ratio, end-to-end delay, and node survivability. By incorporating environmental factors and underwater acoustic channel characteristics into clustering and routing decisions, the proposed framework achieves reliable, scalable, and energy-efficient network operation under dynamic underwater conditions. Future work will focus on evaluating the framework under diverse environmental scenarios, integrating real-time oceanographic data, and exploring lightweight machine learning techniques for predictive network adaptation. In addition, energy harvesting, security enhancement, fault tolerance, and large-scale experimental validation will be investigated to further improve the practicality of the framework for long-term underwater monitoring applications.

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Abbreviations

The following abbreviations are used in this manuscript

Abbreviation	Full Form
UWSN	Underwater Wireless Sensor Network
FCM	Fuzzy C-Means
CH	Cluster Head
GSA	Gravitational Search Algorithm
EHO	Elephant Herding Optimization
COSEN	Chain-Oriented Sensor Network
SNR	Signal-to-Noise Ratio
BER	Bit Error Rate
GWO	Gray Wolf Optimization
FCMMFO	FCM + Moth-Flame Optimization
MCR-UWSN	Metaheuristic Clustering and Routing UWSN
EE-UWSNs	Energy-Efficient Protocol for UWSNs
WDFAD-DBR	Weighting Depth and Forwarding Area Division-Depth Based Routing
EESLEPRP	Energy-Efficient Sea Lion Emperor Penguin Routing Protocol

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